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Performance Analysis of Vehicular Ad-hoc Networks

Ph.D. Dissertation Booklet

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1 Overview

The user demand in computer networks has been increasing exponentially in the last decades. New technologies have been added to the network devices (i.e., routers, switches) of computer networks to manage the increasing demand in proper way [1]. The complexity in management, routing, use of network resources (i.e., bandwidth), and so on, are important challenges, they are the starting points of many research work. In computer and telecommunication networks the overall traffic is a mixture of packet flows having different quality demands. Some packets are urgent, while some others can tolerate delay better. Most modern communication protocols have a field in the packet header indicating to which class the packet is belonging to (like the class of service (CoS) field in the Ethernet frame header and the DiffServ code point (DSCP) in the IP header). Packet schedulers in the network devices (switches, routers) need to take this information into account to provide the necessary quality of service. A popular multi-class scheduling discipline for this purpose is the weighted fair queueing (WFQ) service. In such systems the packets belonging to different traffic classes are stored in separate queues before they get transmitted. The total service capacity is shared among the classes according to the weights associated with the queues: The higher the weight of a traffic class is, the higher service rate it gets. The WFQ schedulers are work conserving, thus the total service capacity is always distributed among the classes that are currently active. The weights provide a flexible way to express the importance of the traffic classes. However, the analysis of the WFQ schedulers is challenging.

Moreover, the modern communication systems have appeared in many fields of our life. These technologies are present anywhere and anytime. One approach of commutation systems is called Mobile Ad-hoc Network (MANET) [3], which is a wireless system without central control, which consists of freely moving nodes. MANET is a self-configuring wireless network. A MANET comprises of mobile nodes, a router with multiple hosts and wireless communication devices. The telecommunication devices are based on wireless transmitters, receivers, and smart antennas within radio coverage. A new technology based on MANET is called vehicular ad-hoc network (VANET). VANET make the communication between the vehicles and exchange of information possible. Still, these communication services face many challenges due to different parameters (i.e., delay in received information, interference, etc.) lead to reduce the efficiency of communication systems [4]. In VANET, the vehicle-to-vehicle communication is often abbreviated as V2V, while the vehicle-to-infrastructure communication is usually referred to as V2I communication. As there are increasing number of vehicles on the roads, such a communication platform has many benefits, including

- decreasing the number of accidents caused by driver inattention,
- increasing the efficiency of transportation by platooning,
- propagating information about events on the highways,

- etc.,

thus the major objective is to increase both the efficiency of transportation and the road safety. The first step in realizing this objective is to equip vehicles with communication capabilities, thus, in the first period, only vehicles will be able to communicate, we can only talk about V2V communication. In this scenario, vehicles close enough to each other form so-called *clusters*, and only vehicles belonging to the same cluster can exchange messages with each other. The most efficient solution to improve the connectivity is to introduce infrastructure nodes, so-called *road-side units (RSUs)*, which can also participate in the message forwarding process (both V2V and V2I communication, [13]). Unfortunately, due to the high cost, complexity and lack of cooperation between government and private sectors the deployment of RSUs is slow [14]. There are two kinds of RSUs: in the *unconnected* case the RSUs are not able to communicate with each other, while in the *connected* case there is a direct communication channel (apart from the radio) between them. Due to the aforementioned factors, RSUs will probably be unconnected in the first deployed VANET systems.

2 Problem statements

Telecommunication devices in general and in VANETs are facing many *challenges that are caused by constraints* such as limited buffer capacity, narrow radio bandwidth, short radio coverage, cost of established communication infrastructure. These limitations affect the performance, such as resource consumption, delay of data delivery, speed of message propagation, and network reliability. To overcome these limitations these systems should be optimized based on economical and user satisfaction. The mathematical analysis can play an important role in the optimization of these systems based on stochastic models, it can help in understanding the behavior of these systems better.

Our research work has been organized along the following four problem statements.

2.1 Queueing system associated with network devices

The weighted fair queueing (WFQ) service discipline provides a flexible way to share bandwidth among two or more traffic classes. Some variants of the basic WFQ principle are used in the practice in computer networks in routers, switches, etc. Unfortunately, the analytical modeling of the related queues turned out to be notoriously difficult.

The first problem that is associated with telecommunication devices (i.e., routers, switches, etc.) have many challenges and limitation as follows:

- There is no accurate formula for the mean response times that could be used to optimize the usage of network resources.

- Such a formula could enable the dynamic assignment of weights associated with the classes depending on the current network conditions.

2.2 Alert message propagation in VANETs without RSUs

To provide sufficient quality of service, it is important to develop analytical models to calculate various performance measures related to the message propagation. For instance, by computing how far the message propagates, and how long it takes to deliver a message to the vehicles, proposed model can help the drivers to take appropriate decisions on time. Having the message received, the driver can leave the road before reaching the accident and the corresponding traffic jam, or vehicles can maintain a suitable distance between each other to avoid accidents.

VANETs can have the following issues:

- The delivery delay of (alert) messages exchanged between the vehicles can be too high.
- There are no stochastic models available for the stationary and transient solutions of the message propagation distance.

2.3 Alert message propagation in VANETs with disconnected RSUs

The appropriate position of the road-side units (RSUs) can play an important role in the alert message propagation. Appropriate positioning of RSUs can increase the speed of message propagation and decrease the number of accidents, and that will lead to increased safety of the transportation system.

Problems to solve in VANETs with RSUs are:

- There is no formula providing the asymptotic message propagation speed as the function of the RSU distance. Such a formula could be useful to determine the optimal distance between RSUs and to calculate the effect of speed restrictions on message propagation.
- The transient distribution of the distance where the message is available is unknown.

2.4 Failure of the Poisson process for modeling vehicle inter-arrival times

The Poisson process has been used in the literature for a long time to model the inter-arrival times of the vehicles. The reason for this modeling choice is not its validated correctness, but its analytical simplicity; many useful performance measures can be expressed analytically when Poisson traffic is assumed. The Poisson process is, however, not a good model for the vehicular traffic in the vast majority of the cases. Due to the failure of the Poisson process in the modeling of vehicular traffic, different stochastic models, such Markovian Arrival Processes (MAPs) should be investigated.

Challenges in this field:

- MAPs are not commonly known by the VANET community.
- No results are available for the message propagation in case of MAP vehicle arrival process.

3 Research Objective

As mentioned in Section 2, many challenges in the telecommunication system can be solved by introducing accurate analysis based on the mathematical model, that I used in my research work.

Telecommunication system devices have a stream of packets as input, like many other systems such as queueing systems, electrical systems, and many other examples. The accurate description of the input stream of these systems is important to obtain accurate performance measures, however, in many cases the Poisson arrival process is used due to its simplicity. We also use Poisson arrival process in Chapters 2, 3 and 4. Furthermore, when the Poisson model is not accurate enough, I can describe the input stream with the extension of the Poisson process, called the Markovian Arrival Process (MAP), as I proposed in Chapter 5.

The main objective of my research is to provide new and efficient performance analysis methods for self-organized networks. The proposed models make it possible to identify what kind of key performance indicators are available to make reconfiguration decisions leading to minimal cost (i.e., channel bandwidth), improved quality of service, development of robust analytical models for the intelligent transportation system. The proposed solution describes the aforementioned problems in Section 2 as follows. *In the telecommunication systems, the packet scheduling algorithms* (i.e., weighted fair queueing) become an important part of buffer management in these devices to improve the performance.

In the network devices of self-organized networks the parameters of the WFQ packet scheduler can be adjusted the scheduler on-the-fly to ensure that the quality requirements are met in changing traffic characteristics. To support this functionality it is important to have a fast algorithm for the analytical calculation of the main performance measures. Such an algorithm can also be used to check the sensitivity of the WFQ scheduler on the traffic characteristics. This objective is elaborated in Chapter 2.

Intelligent transportation systems (ITS) are becoming more and more important nowadays, motivating my research work to develop analytical models to investigate realistic communication systems based-on vehicular ad-hoc networks (VANETs). Providing assistance to drivers on the road based on alert messages received from other vehicles in an appropriate time can help in accident avoidance, as proposed in Chapter 3.

Furthermore, *road-side unit placed in the appropriate position on the highway* increase the efficiency of the transportation systems and road safety by contributing to the transferring of messages. High enough alert message propagation speed can decrease the number of accidents on the road. The solution proposed in Chapter 4 can be used to characterize the dynamics of communication and support the planning process of VANETs based-on disconnected RSUs.

Another objective of my work is *to introduce MAPs to model vehicle inter-arrival times*, when the Poisson arrival model turns out to be inaccurate. In most of the literature regarding VANET technology, the Poisson arrival model is considered as the vehicle's arrival process, but this model does not hold in several cases. Multiple statistical investigation (i.e., probability density function, SCV, and correlation) applied on the realistic data has shown that the Poisson model does not fit for VANET technology in many cases. The properties of the message propagation in VANET, including the distance how far the messages can get, are affected by many parameters, such as the radio channel, the communication protocols but also the traffic model of the vehicles. This fact motivated my research work to use MAPs for vehicle arrivals as proposed in Chapter 5.

To give an understanding of the main parts of the dissertation and their relation with each other, the schematic diagram in Figure 1 shows the contributions of the dissertation.

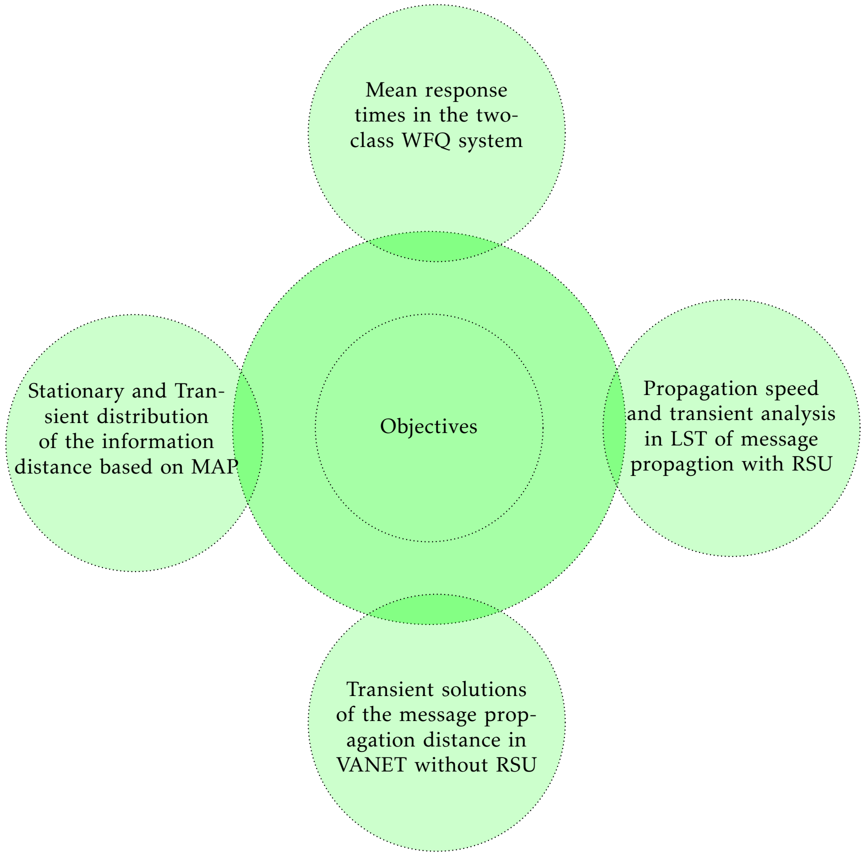

Figure 1: Contributions of the dissertation

4 Research Methodology

The methodology used in our research and problem investigation follows two main approaches: analytical or mathematical and simulations; however, some parts of the proposed solution have been validated by real measurement data as well. All the results in the dissertation are based on some theorems of probability theory, telecommunication systems, traffic engineering, and queueing theory. To implement the analytical methods various numerical algorithms were necessary to evaluate integrals, differential equation, etc.

The proposed solutions have been verified with several simulations setups. In Chapter 2, I modified the Omnet++ simulation (a discrete event simulation framework [15]) with the proposed algorithm, to verify the Matlab implementation. The environment of Omnet++ simulation is flexible enough to extend the proposed solution into multiple classes and run it with different parameters.

Furthermore, the proposed solution in Chapter 3 was tested with Omnet++, too, together with two additional simulation tools called the Simulation of Urban MObility (SUMO, [8]) and Vehicles in Network Simulation (Veins, [12]). Moreover, the results of the Matlab program in Chapters 4 and 5 were verified by a custom developed Simulator tool based on C++ language, this tool can be easily executed with different parameters.

5 New Scientific Results

5.1 Thesis I : Approximate analysis of the two-class WFQ scheduler

I have presented a simple explicit approximation formula for the mean response times in the two-class weighted fair queueing system. While there are some queueing considerations behind the results, the approximation is mostly based on an algebraic approach. The accuracy of the approximation is reasonable, better than past methods found in the literature. The method is described in details in Chapter 2 of the dissertation. The publication associated with Thesis I is [C1].

I consider the two-class weighted fair queueing system. The customers are arriving according to a Poisson process with parameters λ_1 and λ_2, and are directed to two separate queues according to their class. The service times are exponentially distributed with (class independent) parameter μ. The server is shared among the two customer classes, controlled by weights w_1 and w_2. According to the ideal weighted fair queueing policy, both the class 1 and class 2 queues are served in parallel, if both kinds of customers are present in the system: class 1 is served with rate $\mu \cdot w_1/(w_1 + w_2)$, while class 2 is served with rate $\mu \cdot w_2/(w_1 + w_2)$. If one of the queues is idle then the total service capacity is given to the other class.

Let us denote the mean response times of class 1 and class 2 customers by $E(T_1)$ and $E(T_2)$. Due to the conservation law $\rho_1 E(T_1) + \rho_2 E(T_2) = \rho E(T_{FCFS})$ it is enough to focus on a single customer class, class 1, the mean response time for the other traffic class can be expressed from the conservation law. An other feature of the system that I am going to exploit is that the two weight parameters w_1, w_2 defining the system are redundant, it is enough to set $w_2 = 1$ and investigate the behavior of the system as the function of w_1.

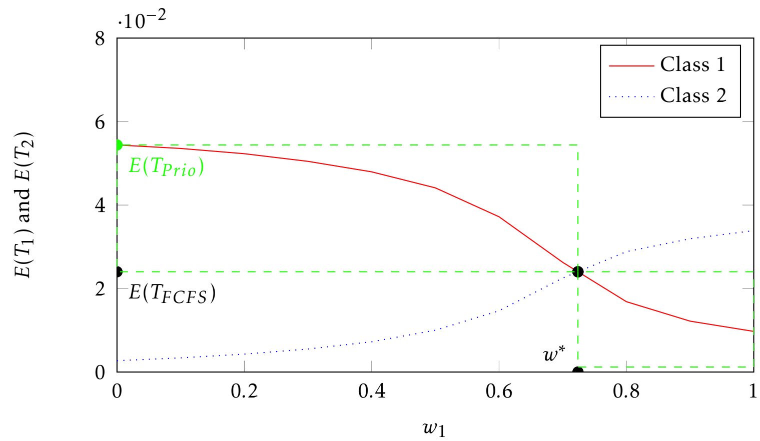

Figure 2: The mean response times as the function of w_1 ($\mu = 0.0012$)

Figure 2 depicts the mean response times as the function of w_1 in a particular example. Observe that if $w_1 = 0$ then the system behaves like a preemptive priority queue with class 1 being the low priority class, hence $E(T_1) = E(T_{Prio})$. At the other hand, when $w_1 \to \infty$, class 1 has exclusive access to the service capacity. The point where the curves of class 1 and class 2 meet plays an important role in our approximation. In this point $E(T_1) = E(T_2)$ holds, the conservation law implies that $E(T_1) = E(T_2) = E(T_{FCFS})$. The weight belonging to this point is denoted by w^*. Based on this point the plot of class 1 on the figure can be divided to two rectangular regions (denoted by dashed lines). Due to the symmetry of the system, I assume that $w_1 \leq w^*$ holds, the role of the two classes can be swapped in the opposite case.

The approximation for the response times consists of two components:

- *The approximation of w^*.* This is the only unknown parameter to fully characterize the region marked by dashed lines in Figure 2. The top left point is given by $w_1 = 0, E(T_1) = E(T_{prio})$, and the bottom right point is located at $w_1 = w^*, E(T_1) = E(T_{FCFS})$.
- *The approximation of the shape of the response time curve.* Based on many simulation experiments I found that w^* is very close to the inflection point in most of the cases (except if the utilization is extremely low). Hence, $E(T_1)$ inside the dashed region is typically monotonous. The bend of the curve depends on ρ_1 and ρ_2, and it is also subject to approximation.

Based on simulation experiments I found the following approximation for w^* accurate enough (see Chapter 2 of the dissertation for more details):

$$w^* = \left(1 - \frac{\rho_1}{\rho_2}\right) \frac{\rho_1 + \rho_2 - 1}{\rho_1 - 0.42\rho_2 - 1} + \frac{\rho_1}{\rho_2}. \tag{1}$$

To express the scaled mean response time

$$\hat{E}(T_1) = \frac{E(T_1) - E(T_{FCFS})}{E(T_{Prio}) - E(T_{FCFS})}, \tag{2}$$

I use the approximation

$$\hat{E}(T_1) = \frac{w_1/w^* - 1}{(2\rho^{6\cdot|r-0.25|^{3.2}+2} - 1)w_1/w^* - 1}. \tag{3}$$

In general, the proposed approximation managed to achieve very accurate results. In the extreme cases, when the utilization is high and the load is very asymmetric, the accuracy is worse, while in the more "balanced" cases the accuracy is better. Among the scenarios I investigated, the results were the worst with parameters $\rho = 0.95, r = -0.82$. The mean response times as the function of w_1 are depicted in Figure 3. The reason of the sub-optimal performance is that under such a high load the inflection point of the curve does not coincide with w^*. However, the results are still much better than the ones obtained by [5].

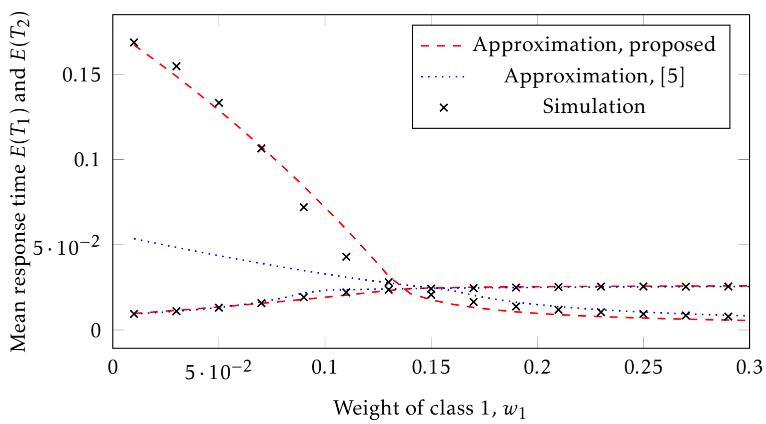

Figure 3: The worst results obtained by the approximation, $\rho = 0.95, r = -0.82$ ($\mu = 0.0012$)

Figure 4 present the typical accuracy of the proposed method. The weights w^*, where the curves cross each other, are captured almost exactly. The approximation of the bend of the curve has some error, but it is much more accurate than the error of [5].

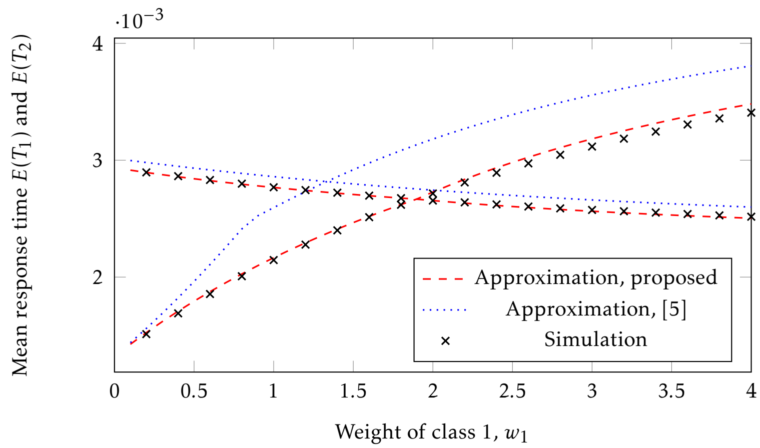

Figure 4: Comparison with parameters $\rho = 0.55$ and $r = 0.67$ ($\mu = 0.0012$)

5.2 Thesis II : Transient analysis of the alert message propagation on the highway in VANET

I assume that the arrival process of the vehicles is a Poisson process (with intensity parameter λ), which is a common assumption made by the waist majority of the related publications, including [17], [18]. All vehicles are assumed to have the same, constant speed, denoted by v. For the radio communication, I assume that all vehicles communicate according to the IEEE 802.11p standard. The direction of the vehicles is constant, and it is one-directional. Assume an event occurs on the highway at position A. This position is assumed to be fixed, and messages advertising the event are generated continuously for a long time.

I have derived the stationary and transient solutions of the alert message propagation distance. I validated the analytical results with simulation (Veins and SUMO within OMNET++). I have proposed an accurate approximation to take into account the length of the traffic jam caused by an accident as well. It is described in details in Chapter 3 of the dissertation, the corresponding publication is [J1].

In case of Poisson vehicle arrival process and constant speed the distance between the vehicles is exponentially distributed with parameter $\vartheta = \lambda/v$.

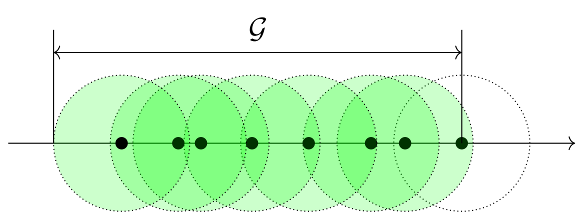

Figure 5: A cluster of informed vehicles

A set of vehicles, where the distance between subsequent vehicles in the set is less

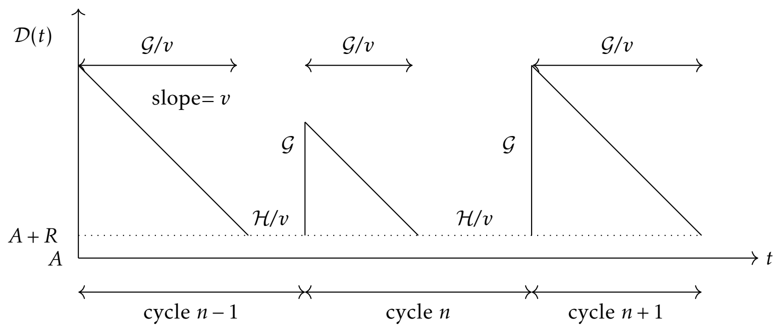

Figure 6: The evolution of the information distance $\mathcal{D}(t)$

than R, is called a *cluster*. The random variable $\mathcal{G}$, referred to as the *cluster length*, that plays an important role in the analysis. $\mathcal{G}$ represents the distance between the position of the first vehicle in the cluster and the last position where the alert information is available, that is, the position of the last vehicle plus R (see Figure 5). The complementary cumulative distribution function (ccdf) of $\mathcal{G}$ is $G(x) = P(\mathcal{G} > x)$, and it satisfies the recursive expression

$$G(x) = \begin{cases} 1, & \text{if } x \le R, \\ \int_{y=0}^{R} \vartheta e^{-\vartheta y} G(x-y)\, dy, & \text{if } x > R. \end{cases} \tag{4}$$

The first term corresponds to the case when x is close enough to the message source to receive the message directly. In the second case the vehicle that is the closest to the message source falls into the coverage area (in distance y); it receives the message and starts broadcasting it, hence the message has to take only the remaining $x - y$ distance to reach the target.

I study the information propagation distance $\mathcal{D}(t)$, that is the position of the last car measured from A having the message received at time t, plus R (the radius of its radio coverage). I characterized the ccdf of the transient behavior of the process $\mathcal{D}(t)$, that is, $F(t,x) = P(\mathcal{D}(t) > x)$ for $x \ge R$. Note that this distribution has probability mass at $x = R$, $\mathcal{D}(t) = R$, which occurs when there are no vehicles on the highway having the message received.

In the next theorem I characterize the properties of $\mathcal{D}(t)$.

Theorem 5.2.1. *The transient ccdf $F(t,x)$ satisfies the partial differential equation (PDE) for $x > R$*

$$\frac{\partial}{\partial t}F(t,x) - v\frac{\partial}{\partial x}F(t,x) = \lambda(1 - F(t,R_+))G(x-R), \tag{5}$$

where $F(t,R_+)$ denotes $\lim_{x \searrow R} F(t,x)$. For $x \le R$ I have $F(t,x) = 1$.

I demonstrate some studies that can be carried out using the results for the transient behavior. I note that the transient behavior is especially difficult to investigate efficiently by simulation: to compute the message propagation probabilities at a certain time t a huge number of independent simulations must be performed up to time t with different random seeds. On the other hand, based on the numerical solution of the PDE, our analytical formulas, the results can be computed quickly without any numerical issues. Figure 7 depicts the transient ccdf $F(t,x)$ at $t = \{1,2,4\}$ seconds together with the stationary solution $F(x)$. According to the figures, by such high vehicle density, the stationary solution is achieved very fast, in just 4 seconds.

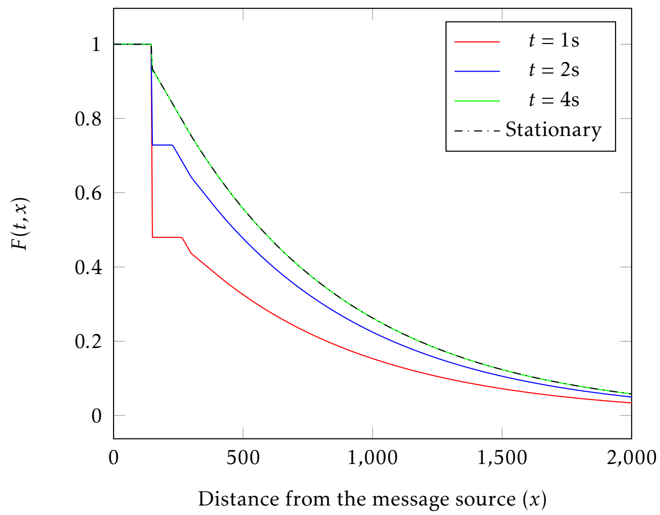

Figure 7: The transient distribution $F(t,x)$ at some time points, $\vartheta = 0.65$, $R = 150$m

To take the effect of the traffic jam into account, I introduced an M/D/1 queueing model. The stationary queue length probabilities $\pi_i = P(\mathcal{X} = i), i \geq 0$ can be obtained by the solution of

$$\pi P = \pi, \qquad \sum_{n=1}^{\infty} \pi_n = 1, \tag{6}$$

where π is the (infinitely long) row vector consisting of probabilities π_i.
The mean queue length by the Pollaczek-Khinchine formula

$$E(\mathcal{X}) = \rho + \frac{1}{2}\frac{\rho^2}{1-\rho} \tag{7}$$

provides a simple explicit solution for the message propagation distance in the presence of the queue, denoted by $\mathcal{B}(t)$, as

$$E(\mathcal{B}) = E(\mathcal{X}) + E(\mathcal{D}). \tag{8}$$

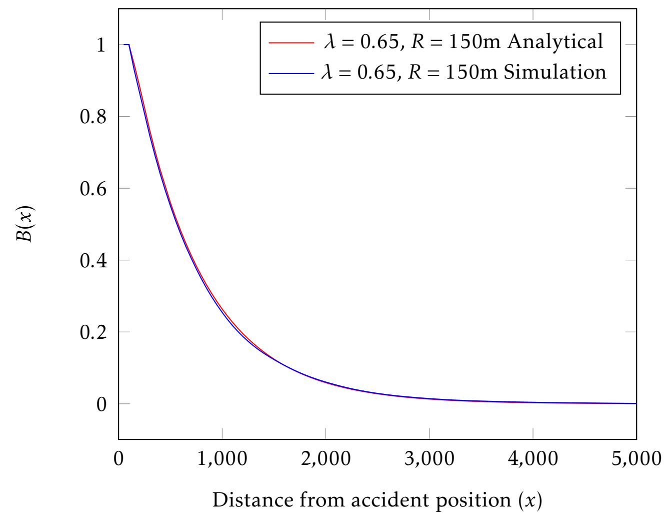

Figure 8: The comparison of the analytical and simulation-based results

The comparison between the analytical and the simulation results is depicted in Figure 8. According to the results, the simple model proposed to approximate the effect of the traffic jam turned out to be reasonably accurate. For the ccdf of $\mathcal{B}$, defined by $B(x) = P(\mathcal{B} > x)$, our approximation is given by

$$B(x) = \sum_{i=0}^{\infty} \pi_i \cdot F(x - i \cdot L), \tag{9}$$

since the length of i cars in the traffic jam is $i \cdot L$, where L is the vehicle length.

5.3 Thesis III : Analysis of the Alert Message Propagation Speed in VANET with Disconnected RSUs

The most efficient solution to improve the connectivity in VANETs is to introduce infrastructure nodes, so-called *road-side units (RSUs)*, which can also participate in the message forwarding process. I consider the message propagation speed on the highway, where messages can be exchanged not only between the vehicles, but also between the road-side infrastructure and the vehicles as well. In our scenario alert messages are generated by a static message source constantly.

5.3.1 Sub-thesis 1: Asymptotic speed of the message propagation based on disconnected RSUs in VANET

I have derived the asymptotic speed of the alert message propagation, and characterized the message passing process between the RSUs. I accomplished numerical investigations with realistic parameters. It is described in Chapter 4 in the dissertation and the associated publication is [J2].

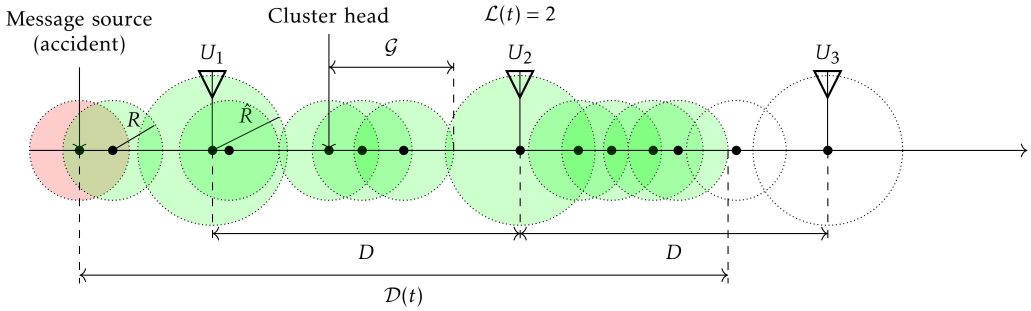

Figure 9: A snapshot of the highway at time t; green color denotes the informed elements

I assume that road-side units (RSUs) are deployed along the highway in an equidistant manner, with the distance between any two adjacent RSUs denoted by D. The radio coverage of the RSUs is denoted by $\hat{R}$, for which $\hat{R} \geq R$ holds. The RSUs are disconnected, which means that there is no direct way of communication between them [11].

Our main goal is the analysis of the asymptotic message propagation speed, C, defined by $C = \lim_{t\to\infty} \frac{E(\mathcal{D}(t))}{t}$ thus, how fast the information propagates back on the highway.

Figure 10 depicts a sample trajectory of $\mathcal{D}(t)$, where the positions of the RSUs are denoted by $U_k, k = 1, \dots$. I first identify renewal time instants in the evolution of $\mathcal{D}(t)$, where the process becomes memory-less, these are the time points where the farthest informed RSU, changes, $\mathcal{Q}_k, k = 1, \dots$.

Random variables $\mathcal{T}_k = \mathcal{Q}_{k+1} - \mathcal{Q}_k, k = 1, \dots$ is the time between renewal instants, and $\mathcal{S}_k, k = 1, \dots$ is the distance between the RSU that was the farthest informed previously and the RSU that got the farthest after getting informed at a renewal instant.

Theorem 5.3.1. *The main result, the message propagation speed is formulated by equation*

$$C = \frac{E(\mathcal{S})}{E(\mathcal{T})} = v \cdot \frac{D}{\left(\frac{1}{\vartheta} + H(D - 2\hat{R} + R)\right)\frac{1-G(D-2\hat{R}+2R)}{G(D-2\hat{R}+R)} + H(D - 2\hat{R} + 2R) - D + 2\hat{R} - 2R}, \quad (10)$$

where $H(x)$ is the finite integral of $G(x)$, given by $H(x) = \int_0^x G(y)\,dy$.

The new results consider the RSU and vehicle have different radio range $\hat{R} > R$ as shown in Figure 11. The left side of the Figure describes the mean time between renewal instants $E(\mathcal{T})$, increasing RSU distance D lead to greater $E(\mathcal{T})$ as well. At higher traffic rate the clusters are longer, thus the message can reach the next RSUs sooner. The right side of Figure depicts $E(\mathcal{S})$, the mean distance between the RSU that was the farthest informed previously and the RSU that got the farthest after getting informed at a renewal instant. According to the right Figure the relation between D and $E(\mathcal{S})$ is not monotonous. If D is small, more RSUs can get the message when a long

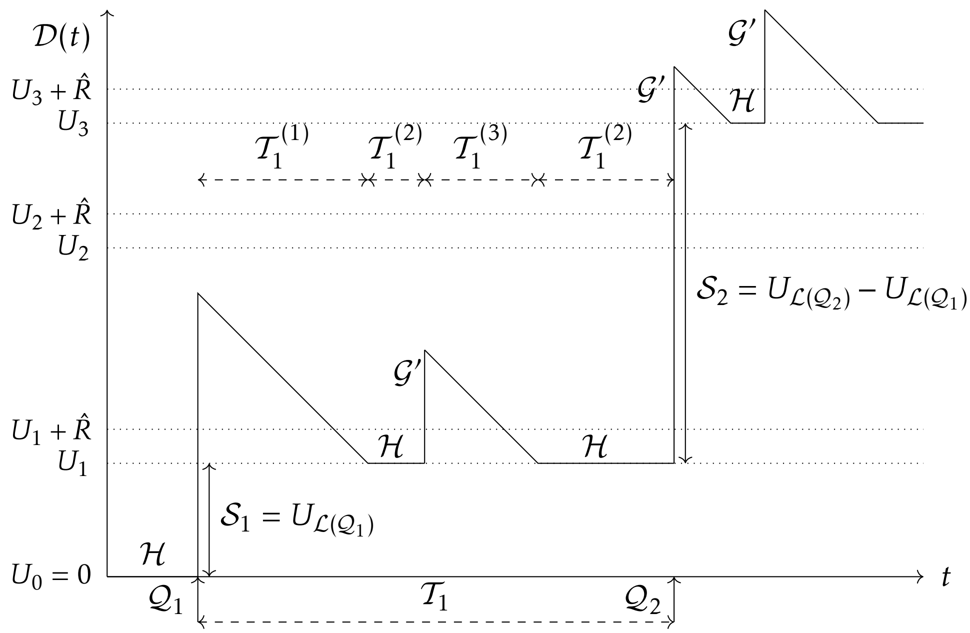

Figure 10: The evolution of the information distance $\mathcal{D}(t)$

enough cluster arrives. If D is big, a lot of time is needed to transfer the message from an RSU to an other one, but once it occurs, the distance the message moved forward is greater.

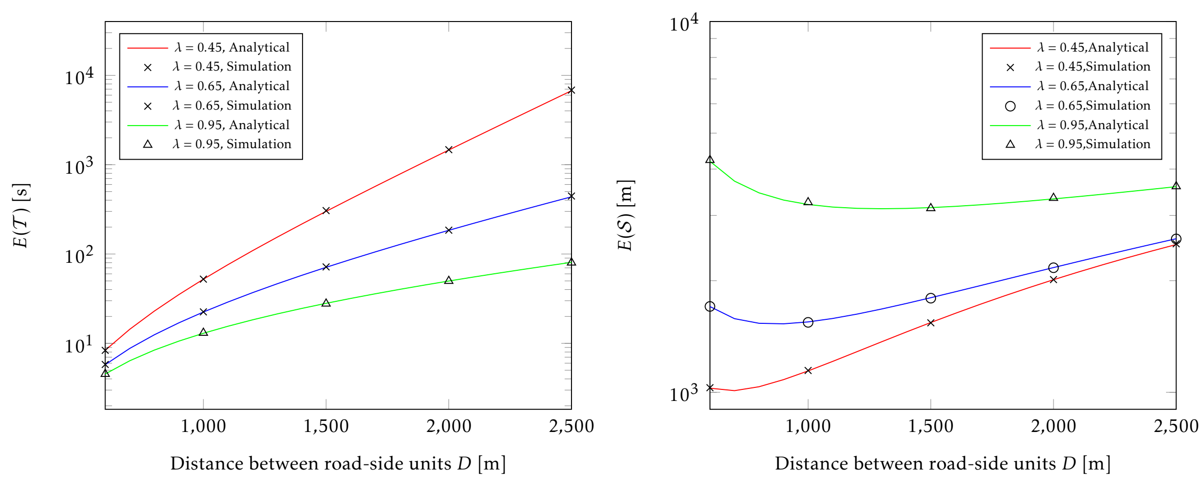

Figure 11: The mean time $E(\mathcal{T})$ and RSU distance between renewal instants $E(\mathcal{S})$

The ratio of $E(\mathcal{S})$ and $E(\mathcal{T})$ gives the speed of message propagation C, The Figure 12 depict speed of information propagate from inform point, the Figure shown speed of that information can be very high when I have different transmission range. The accurate results as shown in Figure 12 based on $R = 150m$ for the vehicles and $\hat{R} = 250m$ with different traffic load that represent by arrival rate parameter λ.

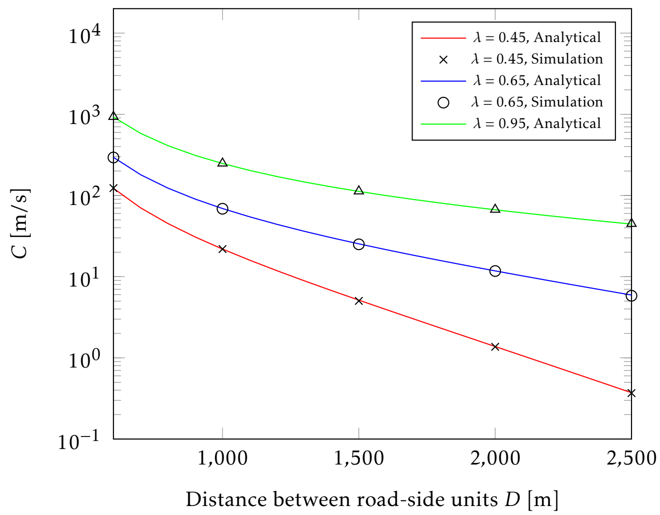

Figure 12: Speed of message propagation

According to our numerical investigations with appropriate RSU distance, greater radio coverage and greater traffic intensity leads to higher message propagation speed. The message propagation speed can be very high, much higher than the speed of counter-flow vehicles. These curves in Figure 12 are useful to find the optimal distance when planning the RSU deployment. The results can be used in the network planning process of VANETs with disconnected RSUs.

5.3.2 Sub-thesis 2: Transient analysis of the message propagation based on disconnected RSUs in VANET

A potential application of VANETs is the propagation of alert messages containing emergency information related to highway accidents. To quantify how efficiently the RSUs and the vehicles disseminate the information, it is important to study the transient properties of the message propagation, thus the probability that the message is available beyond a given RSU after a certain amount of time.

I derived the transient distribution of the distance where the message is available, in Laplace transform domain. It is described in Chapter 4 in the dissertation and the associated publication is [J2].

If random variable $\mathcal{L}(t)$ represents the index of the farthest RSU having the message received, then our aim is to obtain the probability $P(\mathcal{L}(t) = i)$.

Theorem 5.3.2. *The Laplace transform of the transient distribution $L_i^*(s)$ satisfies the following recursion*

$$L_i^*(s) = \begin{cases} \sum_{k=1}^{i} q_k f^*(s) L_{i-k}^*(s), & \text{for } i > 0, \\ \frac{1}{s}(1 - f^*(s)), & \text{for } i = 0, \end{cases} \tag{11}$$

where q_k is the probability that k RSUs receive the message at a renewal instant,

$$q_k = G(D - 2\hat{R} + 2R)^{k-1}(1 - G(D - 2\hat{R} + 2R)), \tag{12}$$

and $f^*(s)$ is the Laplace-Stieltjes transform of the time between two renewal intervals.

Corollary 1. *The double transform of the transient distribution, $L^*(s,z)$, is explicitly given by*

$$L^*(s,z) = \frac{(1 - zG(D - 2\hat{R} + 2R))(1 - f^*(s))}{s(1 - zG(D - 2\hat{R} + 2R)) - s\,z\,f^*(s)(1 - G(D - 2\hat{R} + 2R))}. \tag{13}$$

Figure 13 depicts the Laplace transforms $L_i^*(s)$ for $i = 0, \ldots, 30$ using (11) after applying the CME-based inverse Laplace transform method [6] to get the results in time domain. I have set the parameters to $\hat{R} = R = 250m, D = 1500m$ in this experiment. The distributions are depicted by Figure 13. According to the Figure, after 60 seconds it is most likely that RSU number 4 is the farthest informed RSU, after 90 seconds it is RSU number 10 and after 120 seconds it is RSU number 15.

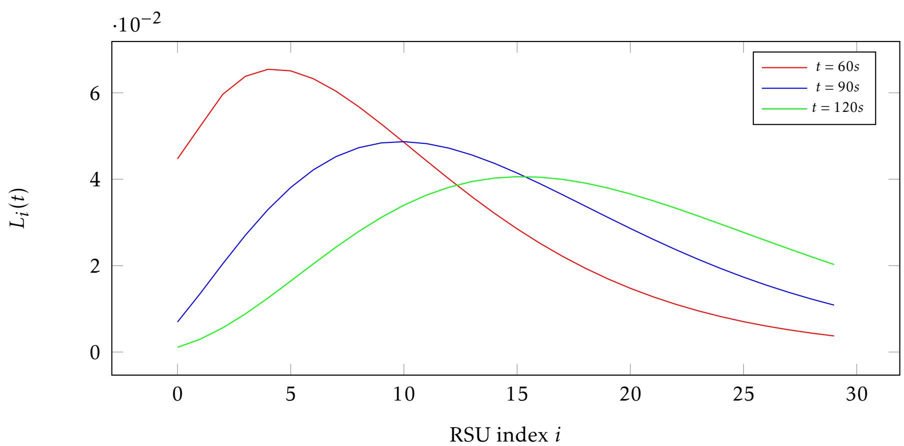

Figure 13: Transient distribution of the farthest informed RSU

5.4 Thesis IV : Analysis of the alert message propagation based on MAP vehicle arrival process

Most papers published on the analysis of message propagation assume that the inter arrival times between vehicles follow a Poisson process; there are very few results

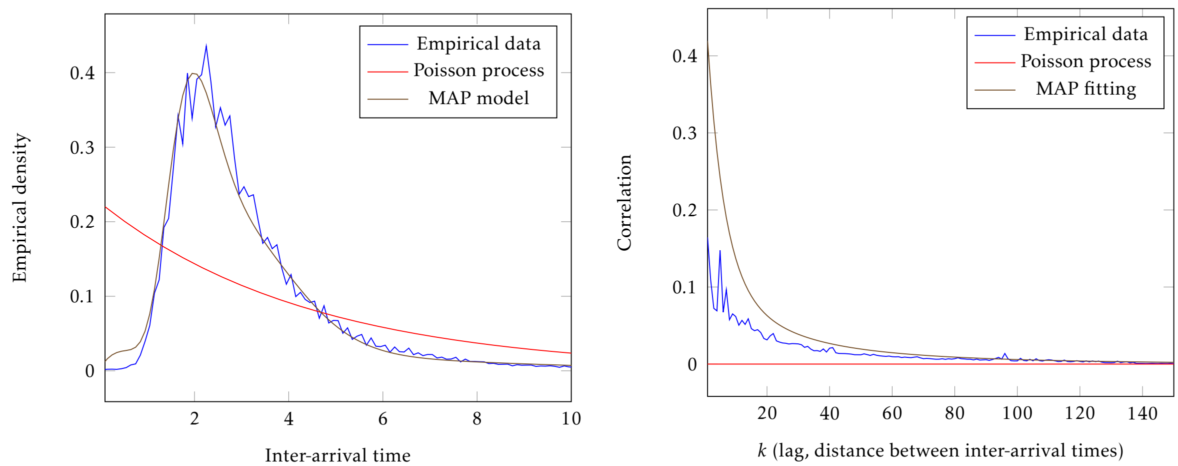

Figure 14: Comparison of the empirical pdfs and lag-k correlations of the vehicle inter-arrival times

available with more general traffic model. In the Dissertation it is shown that the Poisson process is not always suitable for modeling vehicle traffic (see also Figure 14). Instead of the Poisson process, I propose to use the more general Markovian arrival process (MAP) to model the vehicle headway times, and derive the probability that the message propagates beyond a certain distance from the accident under this traffic assumption.

I have a MAP vehicle arrival process that is characterized with two matrices $\boldsymbol{D_1}$ and $\boldsymbol{D_0}$ (matrix $\boldsymbol{D_1}$ contains the rates of those state transitions which are accompanied by a vehicle arrival, and matrix $\boldsymbol{D_0}$ contains the rate of those transitions that do not generate arrival events, they are internal transitions only).

5.4.1 Sub-thesis 1: Analysis of the cluster length

I have derived the properties of the clusters of vehicles are ccdf of the stationary cluster length, the phase-dependent mean value of cluster length, the phase-dependent second moment of cluster length and the delay differential equation (DDE) of the phase-dependent stationary cluster length. The results are described in Chapter 5 in the dissertation and the associated publication is [J3].

I have considered the joint behavior of the *cluster length* $\mathcal{G}$ (see Figure 5) and the phase of the MAP. Namely, I have to keep track of the phase of the MAP at two specific time points: at the time when the first vehicle of the cluster was generated, and at $\mathcal{G}/v$ later (at the end of the cluster).

If the phase of the MAP at time t is denoted by $\mathcal{J}(t)$, and the first vehicle of the cluster was generated at time $t = 0$ (without loss of generality), the complementary cumulative distribution function (ccdf) of $\mathcal{G}$ and the phase at the end of the cluster is defined by $G_{ij}(x) = P(\mathcal{G} > x, \mathcal{J}(\mathcal{G}/v) = j \,|\, \mathcal{J}(0) = i)$, and the corresponding matrix $\boldsymbol{G}(x)$ is defined by $\boldsymbol{G}(x) = [G_{ij}(x)]$.

Before expressing $\boldsymbol{G}(x)$, let us introduce matrix $\boldsymbol{Z} = [Z_{ij}]$ with the transition probabilities of the MAP between the beginning and the end of the cluster as $Z_{ij} = P(\mathcal{J}(\mathcal{G}/v) = j \,|\, \mathcal{J}(0) = i)$.

Novel properties of the cluster of vehicles are described by the following theorems:

Theorem 5.4.1. *Matrix* $\boldsymbol{Z}$ *can be expressed by*

$$\boldsymbol{Z} = (\boldsymbol{I} - \boldsymbol{P} + e^{\boldsymbol{D_0}R/v}\boldsymbol{P})^{-1} e^{\boldsymbol{D_0}R/v} \tag{14}$$

Where the stochastic matrix $\boldsymbol{P}$ containing the state transition probabilities between two consecutive inter-arrival events is obtained by

$$\boldsymbol{P} = \int_0^{\infty} e^{\boldsymbol{D_0}t}\boldsymbol{D_1}\, dt = (-\boldsymbol{D_0})^{-1}\boldsymbol{D_1}. \tag{15}$$

Similar to the results available for the Poisson case (4), by the stochastic interpretation of the system, $\boldsymbol{G}(x)$ can be expressed recursively as

$$\boldsymbol{G}(x) = \begin{cases} \boldsymbol{Z}, & \text{if } x \leq R, \\ \int_{y=0}^{R/v} e^{\boldsymbol{D_0}y}\boldsymbol{D_1}\boldsymbol{G}(x - yv)\, dy, & \text{if } x > R. \end{cases} \tag{16}$$

Theorem 5.4.2. *The phase-dependent mean value of* $\mathcal{G}$ *can be calculated by*

$$\boldsymbol{E}(\mathcal{G}) = (\boldsymbol{I} - \boldsymbol{P} + e^{\boldsymbol{D_0}R/v}\boldsymbol{P})^{-1}\left[(\boldsymbol{I} - \boldsymbol{P})R\boldsymbol{Z} - \boldsymbol{D_0}^{-1}\boldsymbol{Z}v\right] + \boldsymbol{Z}\boldsymbol{D_0}^{-1}v. \tag{17}$$

Theorem 5.4.3. *The phase-dependent second moment of the cluster length can be expressed by*

$$\begin{aligned} \boldsymbol{E}(\mathcal{G}^2) = {} & \boldsymbol{Z}(v\boldsymbol{D_0}^{-1} - R\boldsymbol{I})(2\boldsymbol{P}\boldsymbol{E}(\mathcal{G}) - 2v\boldsymbol{D_0}^{-1}\boldsymbol{P}\boldsymbol{Z}) \\ & + (\boldsymbol{I} - \boldsymbol{P} + e^{\boldsymbol{D_0}R/v}\boldsymbol{P})^{-1}\left[2v(-\boldsymbol{D_0})^{-1}\boldsymbol{P}\boldsymbol{E}(\mathcal{G}) + 2v^2(-\boldsymbol{D_0})^{-2}\boldsymbol{P}\boldsymbol{Z}\right]. \end{aligned} \tag{18}$$

Theorem 5.4.4. *The phase-dependent ccdf of* $\mathcal{G}$ *is the solution of the delayed differential equation (DDE)*

$$\frac{d}{dx}\boldsymbol{G}(x) = \boldsymbol{D}\boldsymbol{G}(x) - e^{\boldsymbol{D_0}R/v}\boldsymbol{D_1}\boldsymbol{G}(x - R), \quad x > R, \tag{19}$$

with boundary condition $\boldsymbol{G}(x) = \boldsymbol{Z}, x \leq R$.

Numerical results are shown in Figure 15. In all of the numerical examples the vehicle speed is assumed to be $v = 36m/s$ (which is the typical speed limitation on

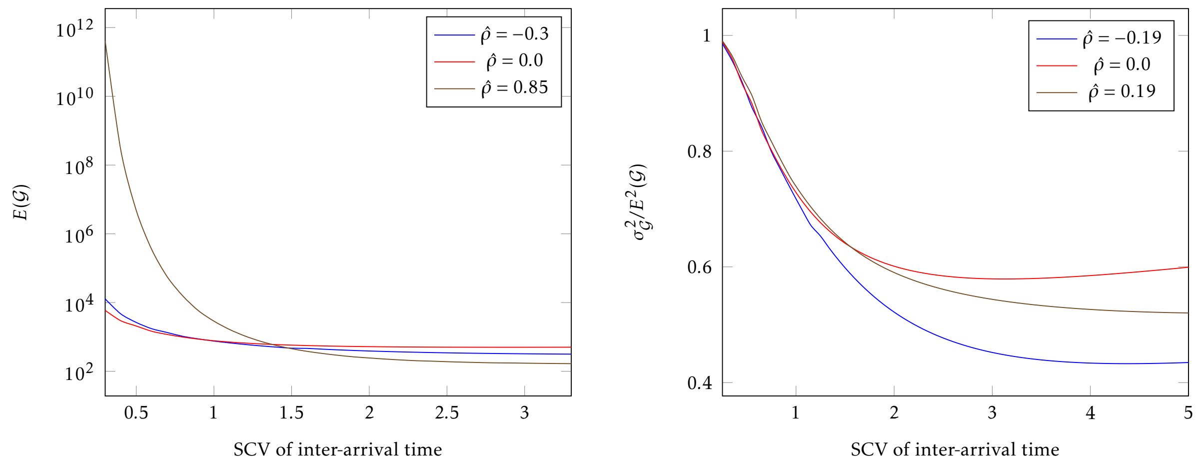

Figure 15: The mean and the SCV of cluster length $\mathcal{G}$

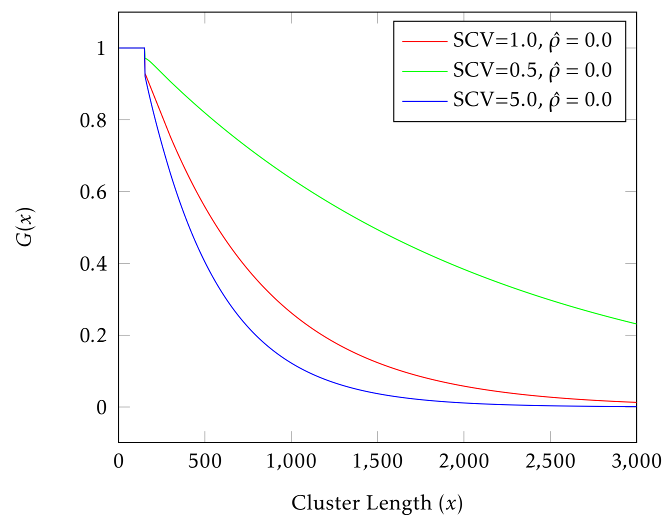

Figure 16: The ccdf of the cluster length distribution with various SCV parameters

highways in many countries), the vehicles density $\lambda = 0.65$ (vehicles/second) , and the radio coverage of the communication is $R = 150m$. As visible from the Figure, the statistics of the vehicle arrival process have a significant impact on the cluster length statistics with different values of lag-1 correlation $\hat{\rho}$ and squared coefficient of variation SCV.

The numerical solution of the DDE defined by Theorem 5.4.4 makes it is possible to investigate the ccdf of the cluster length as the function of the SCV as well.

5.4.2 Sub-thesis 2: Transient analysis of the message propagation

The transient behavior of information propagation distance $\mathcal{D}(t)$ (introduced in Section 5.2) is one of the most interesting measures when the effect of an event/accident is

analyzed since it is important to know how far the alert message gets t time after the accident.
I provide analytical results on the transient properties of the message propagation distance assuming Markovian vehicle arrival process, and show that the more accurate modeling of the vehicle arrival process implies a better approximation of the message propagation distance.

I have derived the transient distribution of the information distance based on Markovian Arrival Process. I validated the analytical results with simulation. The results are described in Chapter 5 in the dissertation and the associated publication is [J3].

The time evolution of the information propagation distance, $\mathcal{D}(t)$ (introduced in Section 5.2) is shown in Figure 6. The trajectory of $\mathcal{D}(t)$ consists of alternating intervals. There are intervals where no vehicles hold the information; the length of these intervals (in distance) is denoted by $\mathcal{H}$. Then, a vehicle enters the range of the accident and gets informed, informing its cluster of length $\mathcal{G}$ as well. This informed cluster will leave the accident in time $\mathcal{G}/v$, followed by another uninformed interval, etc.

The analysis of the joint behavior of $\{\mathcal{D}(t), \mathcal{J}(t)\}$ is easier than analyzing $\mathcal{D}(t)$ alone. The $\widehat{\mathcal{J}}(t)$ as the phase of the MAP at the moment when the cluster present at time t will leave the accident, and define the joint ccdf $F_i(t,x) = P(\mathcal{D}(t) > x, \widehat{\mathcal{J}}(t) = i)$ and the corresponding row vector $\underline{F}(t,x) = [F_i(t,x)]$. The joint probability of being in the uninformed interval and in a certain phase at time t is given by row vector $\underline{\beta}(t) = [\beta_i(t)]$, with elements $\beta_i(t) = P(\mathcal{D}(t) = R, \mathcal{J}(t) = i)$. Note that for the latter quantity I used $\mathcal{J}(t)$ instead of $\widehat{\mathcal{J}}(t)$. Hence, in the uninformed intervals $\underline{\beta}(t)$ follows the evolution of the background Markov chain of the MAP, and when a vehicle enters the range of the accident.

Theorem 5.4.5. *The transient ccdf $\underline{F}(t,x), x > R$ and the probability of an uninformed interval $\underline{\beta}(t)$ satisfy the partial differential equations (PDEs)*

$$\frac{\partial}{\partial t}\underline{F}(t,x) - v\frac{\partial}{\partial x}\underline{F}(t,x) = \underline{\beta}(t)\boldsymbol{D_1}\boldsymbol{G}(x-R), \tag{20}$$

$$\frac{\partial}{\partial t}\underline{\beta}(t) = -\frac{\partial}{\partial t}\underline{F}(t,R) + \underline{\beta}(t)(\boldsymbol{D_0} + \boldsymbol{D_1}\boldsymbol{Z}). \tag{21}$$

The results for the example introduced in Section 5.4.1 are visualized in Figure 17 as a heat map. In line with the expectations, the information distance is always at least R, and the more time elapses since the accident, the higher the probability is that vehicles farther away from the accident receive the message about it. After $t = 300s$ (that is, 5 minutes) the stationary state is almost reached, the distribution of $\mathcal{D}(t)$ does not change significantly.

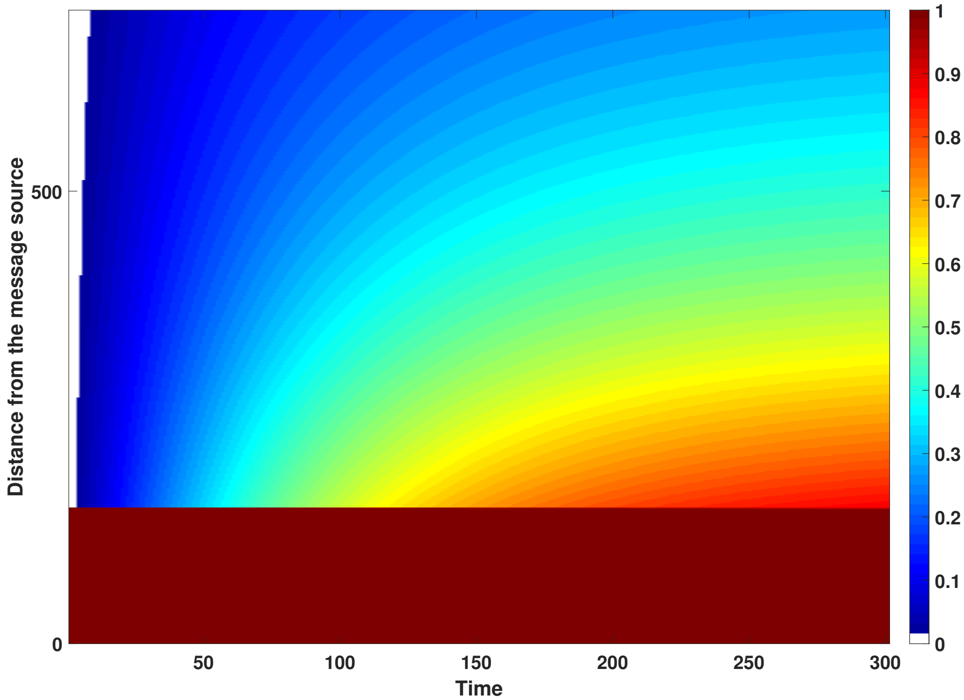

Figure 17: Transient distribution, $F(t,x)$

5.4.3 Sub-thesis 3: Stationary analysis of the message propagation

There is no stochastic model available for the stationary solution of the message propagation distance based on MAP. The stationary solution $\mathcal{D} = \lim_{t\to\infty} \mathcal{D}(t)$ is the distance between the event (i.e. accident on the highway) , A, and the position where the information is available, as seen by an external observer at a random point of time. With other words, when an external observer takes a snapshot of the system, $\mathcal{D}$ represents the distance the message can travel through a chain of vehicles being closer than R to each other, starting in A.

I have derived the stationary characteristics of the information distance based on Markovian Arrival Process. The analysis include the phase dependent ccdf of the information distance, the stationary probability vector of an uninformed interval and the mean information distance. The results are described in Chapter 5 in the dissertation and the associated publication is [J3].

The mean information distance can be expressed from the first two moments of the cluster length $\mathcal{G}$ and from the mean length of the uninformed period $\mathcal{H}$ (see Figure 6).

Theorem 5.4.6. *The mean information distance is expressed by*

$$E(\mathcal{D}) = \frac{E(\mathcal{G}^2)/2}{E(\mathcal{G}) + E(\mathcal{H})} + R \tag{22}$$

The following theorems provide the stationary solution of the phase dependent ccdf of the information distance, denoted by $\underline{F}(x) = \lim_{t\to\infty} \underline{F}(t,x)$, using the stationary phase dependent ccdf of the cluster length $\boldsymbol{G}(x)$.

Theorem 5.4.7. *For $x > R$, the stationary phase dependent ccdf of the information distance is given by*

$$\frac{d}{dx}\underline{F}(x) = -\frac{1}{E(\mathcal{G}) + E(\mathcal{H})}\underline{\gamma}\boldsymbol{G}(x - R), \tag{23}$$

and, for $x = R$, the stationary probability vector of an uninformed interval is the solution of the system of linear equations

$$\underline{\beta}(\boldsymbol{D_0} + \boldsymbol{D_1}\boldsymbol{Z}) = \underline{0}, \quad \underline{\beta}\mathbb{1} = \frac{E(\mathcal{H})}{E(\mathcal{G}) + E(\mathcal{H})}. \tag{24}$$

Finally, the phase independent ccdf of the information distance is given by the next theorem.

Theorem 5.4.8. *The phase independent ccdf of the information distance, $F(x) = \underline{F}(x)\mathbb{1}$, can be expressed by*

$$F(x) = -\frac{\int_0^{x-R} G(y)dy}{E(\mathcal{G}) + E(\mathcal{H})} + \frac{E(\mathcal{G})}{E(\mathcal{G}) + E(\mathcal{H})}, \tag{25}$$

for $x > R$. For $x \leq R$ I have that $F(x) = 1$.

Some numerical examples are shown in Figure 18 (the parameters are the same as before). On the left side of Figure 18, the mean information distance is depicted assuming different SCV and correlation values, based on Theorem 5.4.6. According to the right side of Figure 18 higher SCV of the headway time leads to lower message propagation distance, and high correlation decreases the message propagation distance even more.

5.4.4 Results with empirical data

I did experiments with real data as well. Two factors make such a study difficult.

The first difficulty is that there are very few high-quality headway data traces available publicly. The majority of traffic data contains counts over a certain period of time (e.g., number of vehicles detected in an hour), which is not suitable for MAP fitting. For our procedure, I need the exact arrival times of the vehicles (or equivalently, all headway times). The only relevant data set I found was [2], which was based on LIDAR measurements [16]. While this is a fairly large data set, it is still not long enough, since the treatment of such seasonal traffic measurements needs a lot of data. Hence, I decided to ignore the seasonal nature of the traffic and cut out a part of the data consisting of around ≈ 629000 samples where the traffic was approximately stationary.

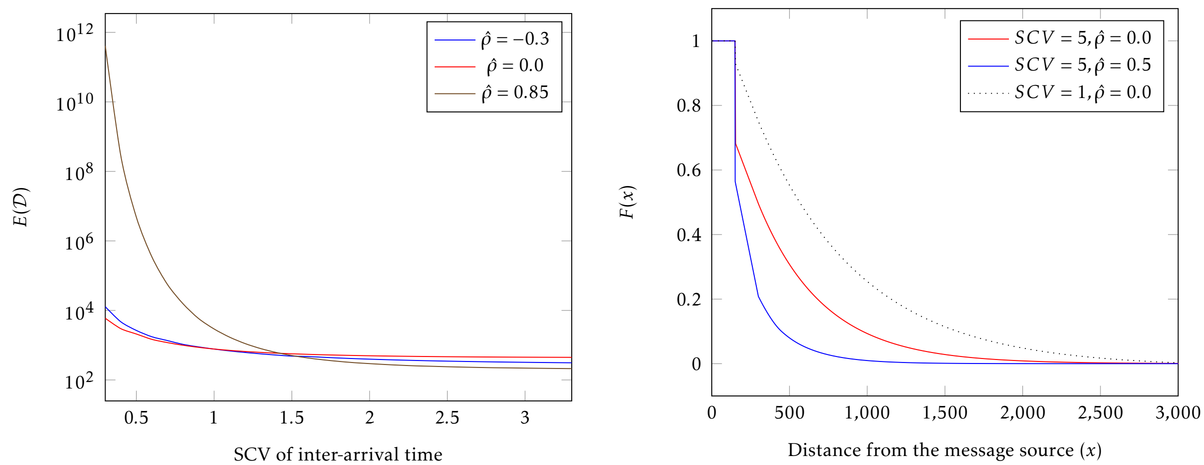

Figure 18: The mean and the ccdf of the stationary message propagation distance $\mathcal{D}$

The second difficulty is that fitting MAPs needs a lot of data. Capturing the characteristics of the density function of the marginal distribution can be accurate with less data, too, but for correlation fitting, especially for higher lags, much more data is needed. This observation is reflected by Figure 14, too, where the density is fitted well, and the lag-correlations are not matching as well. As more headway time data become publicly available, it will be possible to fit MAPs that better represent the real traffic, making our analytical model more accurate. Based on the ≈ 629000 samples extracted from the data set [2], I executed the EM-algorithm published in [7] to create a MAP with 800 states. Even with that many states, the formulas presented in this thesis give instant results. Table 1 compares these analytical results with the simulation results driven by the original measurement data. According to the results, the mean cluster length $E(\mathcal{G})$ is obtained very accurately; the error (the deviation from the simulation results) is below 2%. The Poisson assumption, commonly used in the literature [9,10], gives almost 100% error. The same holds for the mean non-informed periods $E(\mathcal{H})$ as well. However, for the second moment of the cluster length $E(\mathcal{G}^2)$, our method has a significant error, due to the imperfect MAP fitting caused by the overly small data set. Still, the MAP model-based results are not far away from the simulation results, as opposed to the Poisson model-based results, where there is a 100-times difference. The inaccuracy in $E(\mathcal{G}^2)$ implies inaccuracy in $E(\mathcal{D})$, too. Our method gives 4013 meters for the mean message propagation distance instead of 5375 meters, but it is still much better than the Poisson result with 248.6 meters.

I believe that, as more data gets available and more mature MAP fitting methods get developed, the practical relevance of our procedure is going to improve in the future.

Table 1: Experiments with real data

Method \ Metric	$E(\mathcal{G})$	$E(\mathcal{G}^2)$	$E(\mathcal{H})$	$E(\mathcal{D})$
Simulation	495	8.19134+6	290	5375
Poisson Model	248.6306	8.0594e+04	159.9331	248.6306
MAP Model	489.4438	5.9635e+06	282.2731	4013

6 Summary and Future Work

6.1 Summary of Results

Dissertation focused on the self-organized network technology in two main communication system areas: Queueing systems for network devices and Vehicular Ad-hoc Networks. Both of the fields, as mentioned above, have many modeling challenges; therefore. My proposed methods include analytical algorithms and numerical methods, whose accuracy is verified by simulation. The new results can be summarized as follows:

- Explicit approximation formula for the mean response times in the two-class weighted fair queueing system. I developed the analytical method, compared the results with simulation, and proved that the proposed solution is better than the published method found in the literature.

- I introduced new contributions regarding the alert message propagation in VANET systems. Stationary and transient solutions are present in this solution as new results. I validated the analytical results with simulation as well.

- I derived the asymptotic speed of the alert message propagation in VANETs with disconnected RSUs. Different new results are proposed as the speed of message propagation and the transient analysis of message propagation as well. The proposed results can be used in network planning of VANETs.

- The stochastic properties of the arrivals process play important roles on the message propagation in VANET systems. The new results consider the Markovian Arrival Process as a traffic model and I derived different results related to message propagation: the moments and the ccdf of the stationary cluster length, and the stationary and transient distribution of the information distance.

Moreover, I proposed using an M/D/1 queueing model for the traffic jam at the accident to get an improved approximation for the message propagation distance.

On the other hand, I made experiments with simulation both with synthetic and real data to prove that the MAP based vehicle arrival process leads to more accurate results.

6.2 Future Work

The telecommunication systems and Vehicular Ad-hoc Networks are rapidly changing to meet user requirements. Many open issues should be considered before implementing a telecommunication system in the practice. My dissertation deals with some areas of these challenges. I can briefly describe the future work of my research as follows:

- *Adapt the algorithm or develop new algorithms* for more complex packet schedulers and more complex traffic patterns for the schedulers of telecommunication devices (i.e. routers).

- Consider the possibility of *dynamic class switching* in WFQ. Investigate the feasibility of the algorithms in real systems such as 5G devices.

- *Consider the counter-flow* traffic for the alert message propagation model in VANET.

- Extend the research work to the *urban environment* within VANET, not only in highways.

- Collect *more realistic vehicle arrival data* based on a detector loop or video camera. Fitting model based on the large data can give more accurate results.

- *Build a tool based on mathematical result* to support the decisions of road operators.

The new protocols and algorithms are important parts of the alert message propagation in VANET technology, in the future I adapt these protocols to meet the quality of service in intelligent transportation system. As shown in many research work [4], there are different types of services provided through VANET communication systems. Some of these services have low priority compared to emergency message, so in the further research I can consider the *Delay Tolerant Network (DTN)* paradigm to deal with other services such as comfort application (i.e. journey time estimation).

7 Publication

7.1 International Journals and conferences (Peer-reviewed)

- International Journals

[J1] **Mahmood, Dhari Ali**, and Gábor Horváth. "Analysis of the Message Propagation on the Highway in VANET." Arabian Journal for Science and Engineering 44.4 (2019): 3405-3413. (WOS, IF=1.711, Q2)

[J2] **Mahmood, Dhari Ali**, and Gábor Horváth. Analysis of the Message Propagation Speed in VANET with Disconnected RSUs. Mathematics 2020, 8, 782. (WOS, IF=1.747, Q3)

[J3] **Mahmood, Dhari Ali**, and Gábor Horváth. Analysis of alert message propagation on the highway in VANET assuming Markovian vehicle arrival process. International Journal of Communication Systems 2020. (WOS, IF=1.319, Q2)

- **International Conferences**

[C1] **Mahmood, Dhari Ali**, and Gábor Horváth. ”A simple approximation for the response times in the two-class weighted fair queueing system.” International Conference on Analytical and Stochastic Modeling Techniques and Applications. Springer, Cham, 2017. (WOS, Scopus, CiteScore=1.9)

7.2 Other Own publication (Peer-reviewed)

[J4] **MAHMOOD, DHARI ALI**, and RAHUL JOHARI. ”Application of Routing Metrics in Wireless Network.” International Journal of Engineering Science and Innovative Technology (IJESIT) Volume 2, Issue 4, July (2013).

[C2] Johari, Rahul, and **Dhari Ali Mahmood**. ”MeNDARIN: Mobile Education Network Using DTN Approach in North IRAQ.” Proceedings of the International Conference on Internet of things and Cloud Computing. 2016.

[C3] Johari, Rahul, and **Dhari A. Mahmood**. ”GA-LORD: Genetic Algorithm and LTPCL-Oriented Routing Protocol in Delay Tolerant Network.” Wireless Communications, Networking and Applications. Springer, New Delhi, 2016. 141-154.

[C4] Johari, Rahul, and **Dhari Ali Mahmood**. ”GAACO: Metaheuristic driven approach for routing in OppNet.” 2014 Global Summit on Computer and Information Technology (GSCIT). IEEE, 2014.

[C5] **Mahmood, Dhari Ali**, and Rahul Johari. ”Routing in MANET using cluster based approach (RIMCA).” 2014 International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2014.

- **Other publication**

[C6] Reja, Ahmed Hameed, Syed Naseem Ahmad, and **Dhari Ali Mahmood**. ”Study the effect of adding new components on conventional microstrip LPF design.” 2014 International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2014.

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